1.INTRODUCTION

1.1 OVERVIEW

Lung cancer is the leading cause of cancer-related deaths in the world. In the United States, lung cancer claims more lives every year than colon cancer, prostate cancer, and breast cancer combined.

The American Cancer Society's estimates for lung cancer in the United States for 2018 are:

- About 234,030 new cases of lung cancer (121,680 in men and 112,350 in women)
- About 154,050 deaths from lung cancer (83,550 in men and 70,500 in women)

1.2 PURPOSE

Despite the very serious prognosis (outlook) of lung cancer, some people with earlier-stage cancers are cured. More than 430,000 people alive today have been diagnosed with lung cancer at some point. The data is dedicated to classification problems related to the post-operative life expectancy in lung cancer patients: class 1 - death within one year after surgery, class 2 - survival.

We will be using classification algorithms such as Decision tree, Random Forest, KNN, and xgboost. We will train and test the data with these algorithms. From this best model is selected and saved in pkl format. We will be doing flask integration and IBM deployment.

2. LITERATURE SURVEY

2.1 EXISTING PROBLEM

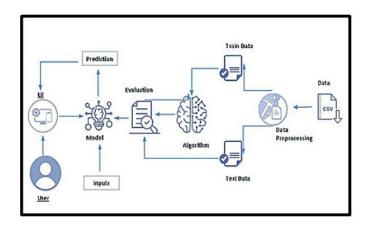
Operative mortality rates have been a topic of great interest among surgeons, patients, lawyers, and health policy administrators. Postoperative respiratory complications are the most common fatality following any type of thoracic surgery. The exact incidence is most contingent upon the preoperative health and lung function of the patient, and we would like to explore and understand how those conditions can drive these complications. One particular metric that has been used to quantify mortality rates in the past has been the thirty-day mortality rate. This metric, however, may not be entirely comprehensive because many patients die shortly after this time period or become very weak, having to be taken to another facility before passing away there. As a result, many of these deaths are severely underreported.

2.2 PROPOSED SOLUTION

The scope of our project is to examine the mortality of patients within a full year after the surgery. More specifically, we are examining the underlying health factors of patients that could potentially be a powerful predictor for surgically related deaths. As mentioned, our feature set includes both continuous and classification data regarding to the patient's health conditions at the time of the surgery. Each patient has 16 variables associated with them Some of the continuous data includes a patients forced vital capacity, the maximum volume their lungs exhaled, size of original tumor, and age at surgery. In addition, we have several classification features such as presence of pain before surgery, haemoptysis before surgery, cough before surgery, whether the patient is a smoker, whether the patient has asthma, and a few others. The classification predicts whether the patient survived the following year long period.

3. THEORITICAL ANALYSIS

3.1 BLOCK DIAGRAM



3.2 HARDWARW/SOFTWARE DESIGNING

To complete this project, you must require following software's, concepts, and packages

- 1. Anaconda navigator and pharm:
- a. download anaconda navigator
- 2. Python packages:
- a. Open anaconda prompt as administrator
- b. Type "pip install numpy" and click enter.
- c. Type "pip install pandas" and click enter.
- d. Type "pip install scikit-learn" and click enter.
- e. Type"pip install matplotlib" and click enter.
- f. Type"pip install scipy" and click enter.
- g. Type"pip install pickle-mixin" and click enter.
- h. Type"pip install seaborn" and click enter.
- i. Type "pip install Flask" and click enter.

4. EXPERIMENTAL INVESTIGATIONS

- 1. Know fundamental concepts and techniques used for machine learning.
- 2. Gain a broad understanding about data.
- 3. Have knowledge on pre-processing the data/transformation techniques on outlier and some visualization concepts.

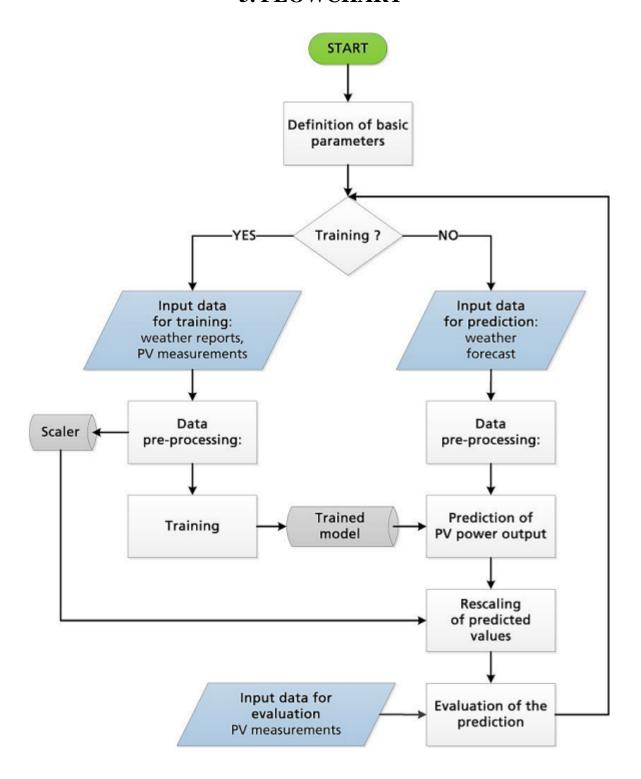
Project Flow:

- 1. User interacts with the UI to enter the input.
- 2. Entered input is analyzed by the model which is integrated.
- 3. Once model analyses the input the prediction is showcased on the UI

To accomplish this, we have to complete all the activities listed below,

- 1. Data collection
 - a. Collect the dataset or create the dataset
- 2. Visualizing and analyzing data
 - a. Univariate analysis
 - b. Bivariate analysis
 - c. Multivariate analysis
 - d. Descriptive analysis
- 3. Data pre-processing
 - a. Checking for null values
 - b. Handling outlier
 - c. Handling categorical data
 - d. Splitting data into train and test

5. FLOWCHART



6. RESULT

INPUT 1



OUTPUT 1



INPUT 2



OUTPUT 2



7. ADVANTAGES & DISADVANTAGES

ADVANTAGES

- Easy and fast to perform
- ML include lack of interpretability, low quality and volume of relevant clinical data

DISADVANTAGES

- Time consuming
- Skill demanding risks of neurological injury

8. APPLICATIONS

Five key applications of ML to cardiac surgery include diagnostics, surgical skill assessment, postoperative prognostication, augmenting intraoperative performance and accelerating transitional research.

9. CONCLUSION

Lung cancer is one of the challenging problems in medical field due to structure of cancer cells. Therefore, the proper medication has to be given to the patient for increasing the survival chances of the patient. Once the cancer is detected, the Thoracic Surgery is one of the best treatment options for the diagnosis of Lung Cancer. The project involves the analysis of the patient's dataset who underwent Thoracic Surgery, and an attempt is made to model a classifier that will predict the survival of the patient post the surgery. The dataset will be trained using four Supervised the Algorithms of Machine Learning that are Decision Tree, Random Forest, KNN, Xgboost. Among the four algorithms used, its observed that all the algorithms give the highest accuracy of 91% compared to the other algorithms data in the future to analyse the system.

10. FUTURE SCOPE

Ultimately, we were able to improve our results by averaging a series of identical and independently distributed trees, which we would like to contrast with boosting, in which the trees would be grown in an adaptive manner specific to the bias (not I.I.D.). We would like to recursively train on the residuals of each misclassification. A next possible step would be to implement the following algorithm (bumping):

- 1. Bootstrap n models (with replacement, forcing even ratios), where number of models = number of features.
- 2. Train n models, with initially one feature per model.
- 3. Test all n models on original data set. Pick the model with lowest error on original data set and define a new residual data set on all misclassified examples.
- 4. Train your next n models on the residual (i.e., boosting) but NO averaging at this point.
- 5. Test on the very original data set and pick the best one. Continue process repeatedly.

Hopefully this will further reduce our variance. In addition, we calculated the optimal feature set as shown above, so it would be interesting to compare different results for all of our implementations if we use only those specific features

11. BIBILOGRAPHY

[Wroclaw University Study] Creators: Marek Lubicz (1), Konrad Pawelczyk (2), Adam Rzechonek (2), Jerzy Kolodziej (2)

- -(1) Wroclaw University of Technology, wybrzeze Wyspianskiego 27, 50-370, Wroclaw, Poland.
- (2) Wroclaw Medical University, wybrzeze L. Pasteura 1, 50-367 Wroclaw, Poland.

Boosted SVM for extracting rules from imbalanced data in application to prediction of the postoperative life expectancy in the lung cancer patients. Applied Soft Computing.

APPENDIX: -

App.py

```
import numpy as np
import pandas as pd
import os
import joblib
from flask import Flask, jsonify, request, render_template, url_for, redirect, Markup

app = Flask(__name__)
joblib_file = "model.pkl"
model = joblib.load(joblib_file)

@app.route('/')
def index():
    return render_template('index.html')
```

```
@app.route("/form", methods=['GET','POST'])
def getform():
  if request.method == "GET":
    return (render template("form.html"))
  if request.method == 'POST':
    if 'submit-button' in request.form:
       diagnosis = request.form["diagnosis"]
       fev = request.form["fev"]
       age = request.form["age"]
       performance = request.form["performance"]
       tnm = request.form["tnm"]
       hae = request.form['hae']
       pain = request.form["pain"]
       dys = request.form["dys"]
       cough = request.form["cough"]
       weakness = request.form["weakness"]
       dm = request.form["dm"]
       mi = request.form["mi"]
       pad = request.form["pad"]
       smoking = request.form["smoking"]
       asthma = request.form["asthma"]
       total
[[diagnosis,fev,age,performance,tnm,hae,pain,dys,cough,weakness,dm,mi,pad,smoking,asthma]]
       #prediction = model.predict(total)
       #input_variables = pd.DataFrame([[performance, dys, cough, tnm, dm]], columns=
['Performance', 'Dyspnoea', 'Cough', 'TNM', 'DM'], dtype=float)
```

```
prediction = model.predict(total)[0]

if int(prediction) == 1:
    prediction = "Patient is at High Risk"

else:
    prediction = "Patient is Not at Risk"

return render_template("result.html", prediction = prediction)

return render_template("result.html")

if __name__ == "__main__":
    app.run(debug=False)
```

train.ipynb

